Space and Time Characteristics of DPR Surface Measurements

S. Durden

Jet Propulsion Laboratory, California Institute of Technology

Collaborator: R. Meneghini (GSFC)

Motivation

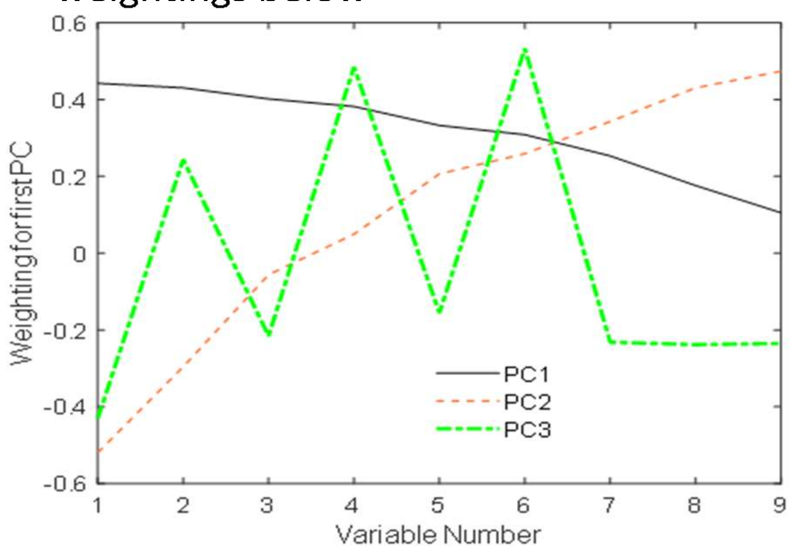
- Main reason for interest in the surface from the GPM DPR perspective is the Surface Reference Technique, which compares precipitating and non-precipitating surface measurements to estimate path integrated attenuation (PIA) – weighted combination of several PIAs, including temporal
- Uses temporal reference database, built by averaging all non-precipitating measurements within each bin in a space/time grid for a given angle, frequency
- For a given land observation with precipitation, the database would contain a reference sigma0:
    - Same day of year
    - Same time of day
    - Same soil moisture, surface water condition, but NOT precipitating (Seto and Iguchi 2007, Turk et al. 2015)
    - Derived from enough samples that mean has small variance
    - Size/location of reference area matches observation area within a few km or less – same land type
- In practice, surface data under non-precipitating conditions is limited
    - Early in missions (TRMM and GPM) have too few observations for high temporal and spatial resolution
    - DPR temporal database started quarterly with 0.5 degree resolution; large number of points in each bin, since more than 6 years except for Ka-band outer swath, which has more than two-years of data
    - By end of TRMM mission, the temporal database was monthly with 0.1 degree resolution; also goal for GPM
- The work here thus looks at two questions
    - What can space/time analysis of sigma0 tell us about needs for the temporal database and possible ways to improve resolution?
    - Can DPR sigma0 be used for applications outside DPR algorithm, e.g., land usage, surface change?

Previous Work

- **Meneghini et al. JTECH 2000:** global (+/-37^o latitude) maps of mean and standard deviation of Ku-band sigma0 at small incidence angles (to 18^o).
    - Notes for SRT that “Despite the simplicity of the basic concept, an assessment of the reliability of the technique is difficult because the statistical properties of the surface return depend not only on surface type (land/ocean) and incidence angle, but on the detailed nature of the surface scattering.”
- **Meneghini and Jones, IEEE GRSL, 2011:** purpose to “understand the way in which the sample standard deviation of the σ0 data changes as a function of spatial resolution, incidence angle, and surface type (land/ocean).”
    - For TRMM 0.1^o and monthly resolutions, noted only about 40 samples per cell (20 at nadir beam)
    - Noted a *decrease* in standard deviation with improving resolution
- **Durden et al., IJRSP, 2012:** used TRMM data to classify surface, showed that dividing surface into classes could potentially reduce sigma0 standard deviations
- **Meneghini et al., IEEE GRSL, 2012:** demonstrated correlation between Ku-band and Ka-band sigma0 over ocean. More recently, similar correlation over land has been confirmed.
- **Meneghini et al., JTECH, 2015:** global maps of Ku/Ka sigma0 data; advantages of dual-frequency SRT.
- **Meneghini and Kim, IEEE TGRS, 2017:** Algorithms to adaptively (stepwise) average data to create temporal database; expand cell size until variance starts increasing. “advantage of variable spatial averaging is that the average standard deviation can be reduced relative to the fixed grid while satisfying the minimum sample requirement.”
    - Follow-on to Meneghini and Jones. Smallest variance occurs when averaging large number of measurements but from a homogeneous area. Expand area of a cell until homogeneity is lost.

Extending Previous Work

- How does sigma0 variation in space and time affect creation of temporal database, utility for surface classification?
- Because of dual-frequency and many-angle nature of data, there are many possible combinations of frequency and angle to investigate
- To understand which most explain the spatial variability:
  - Create a vector of 9 measurements; the first six alternate between Ku-band and Ka-band σ0 at angles of 3º, 6º, and 9º. The final 3 variables in the measurement vector are the Ku-band σ0 measurements at 12º, 15º, and 18º.
  - Form the 9 x 9 covariance matrix and calculate eigenvalues and eigenvectors yields the weightings below

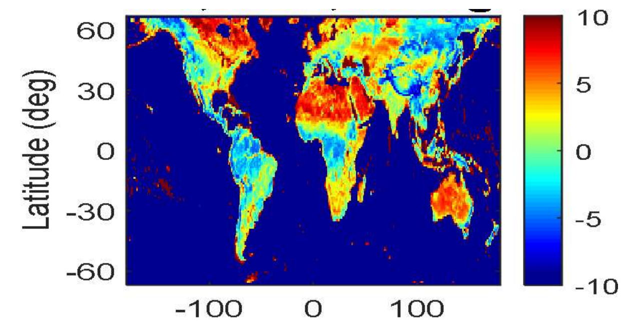


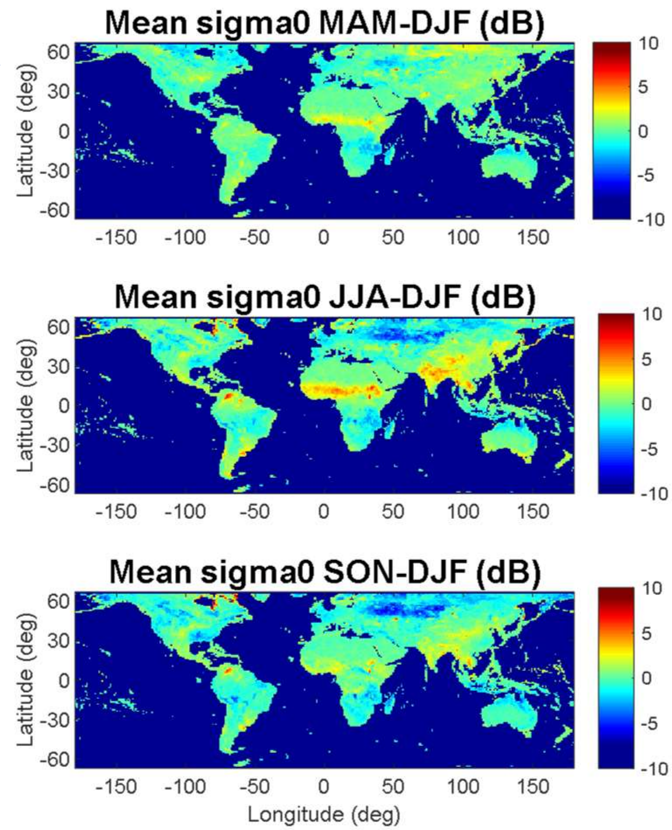
1st – all positive but decrease with angle; also Ka-band tends to be smaller than Ku – 88%
2nd – sign changes beyond variable 4 (Ka-band, 6º), forms difference between small and large angles – 8%
3rd – sign alternates between frequencies; forms dual-frequency ratio, averaged over angle – 2%

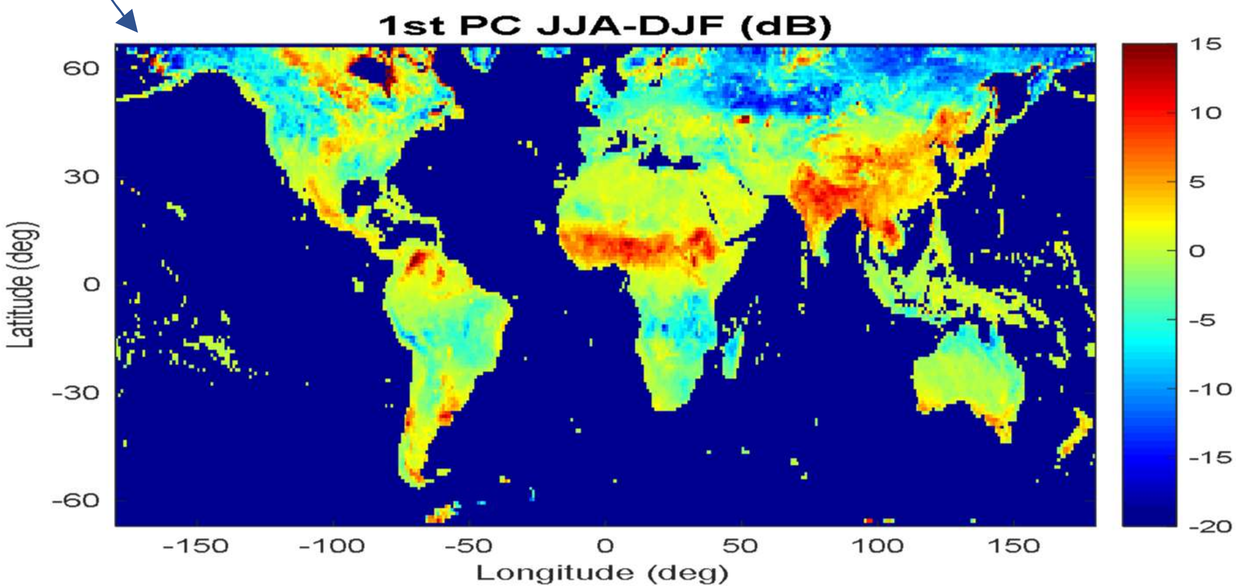
The third point explains the choice of using DFR SRT; it's less sensitive to surface variation than sigma0 (R. Meneghini, personal communication)

Seasonal and Spatial Variation of Mean

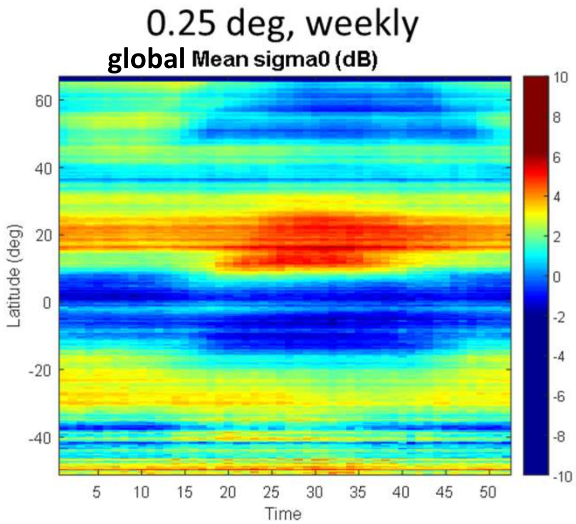
- Significant changes the over space
- Below, 1st PC, 3rd Q minus 1st Q; at right, Ku-band 3°
- PC image is similar to the Ku-band 3° data
- Large seasonal changes can be seen

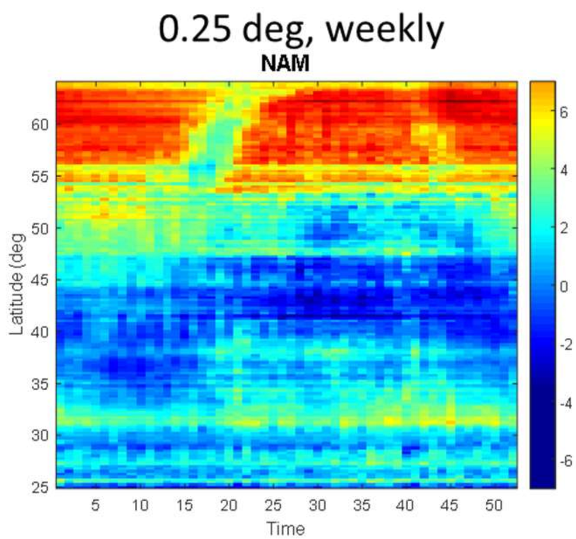




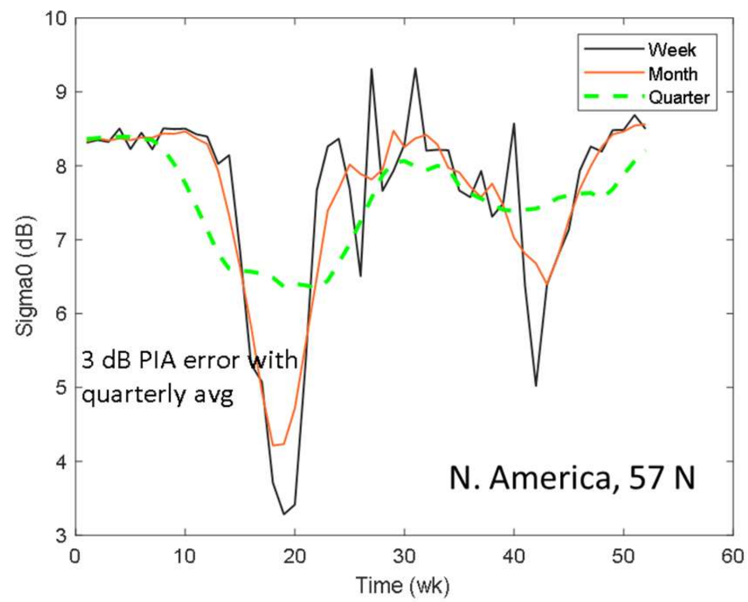


Hovmoller Plots for Seeing Time Variation





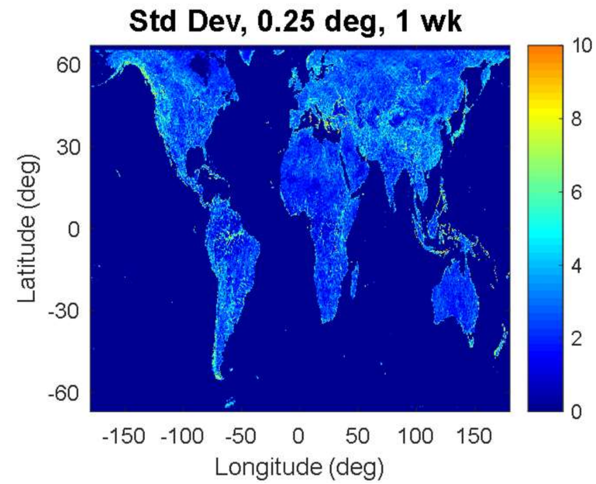
- We take the 3° Ku-band data and average over longitude (land only)
- Upper image is sigma0 versus time (week) and latitude, over most of the GPM coverage area
  - Sigma0 in tropics reaches max in N. Hemisphere in JJA
  - S. Hemisphere tropical max is in DJF
  - N. Hemisphere max at mid/high latitudes is in winter
  - Rather complicated behavior in S. Hemisphere near 40 S; lots of variation with latitude
- Lower image is formed same way but for North America over a narrow range of longitude (100-104) and 25 to 64 N latitude
- Can see sudden drop in sigma0 around week 15 at 55 N; at higher latitudes the sudden drops occurs later – snow melt?
- Plot at right – effect of spatial avg at 60 N

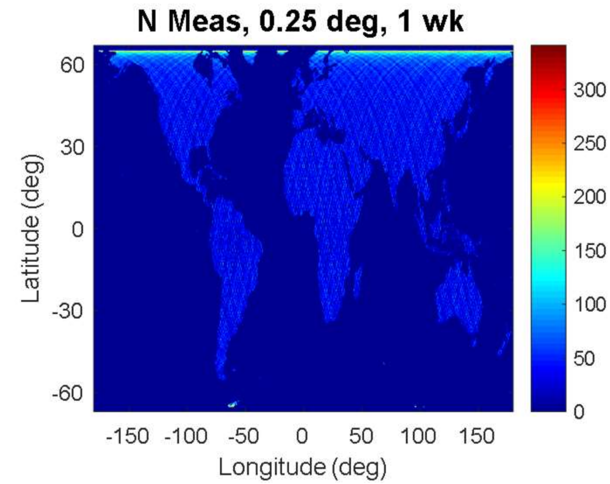


Effects of Space and/or Time Averaging

SD and N meas at each location, at week 14

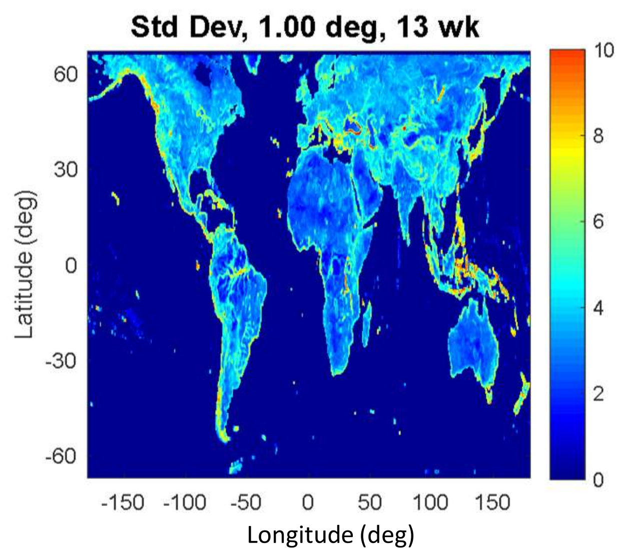
- Mean SD 2.84
- SD of SD 1.45
- Max of SD 18.90

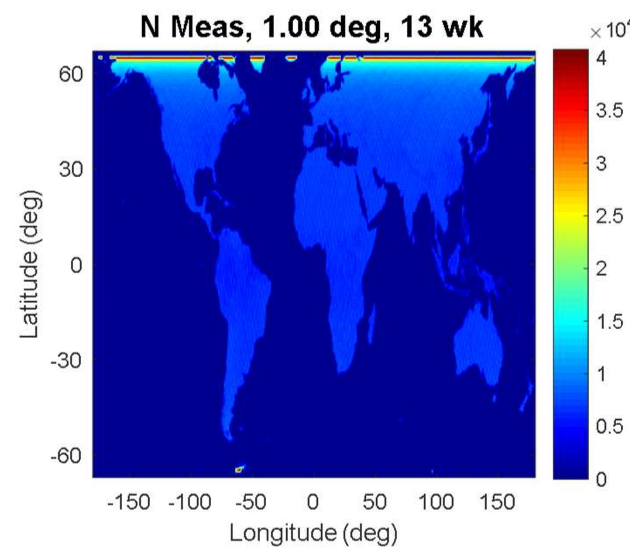




SD and N meas at each location, at MAM

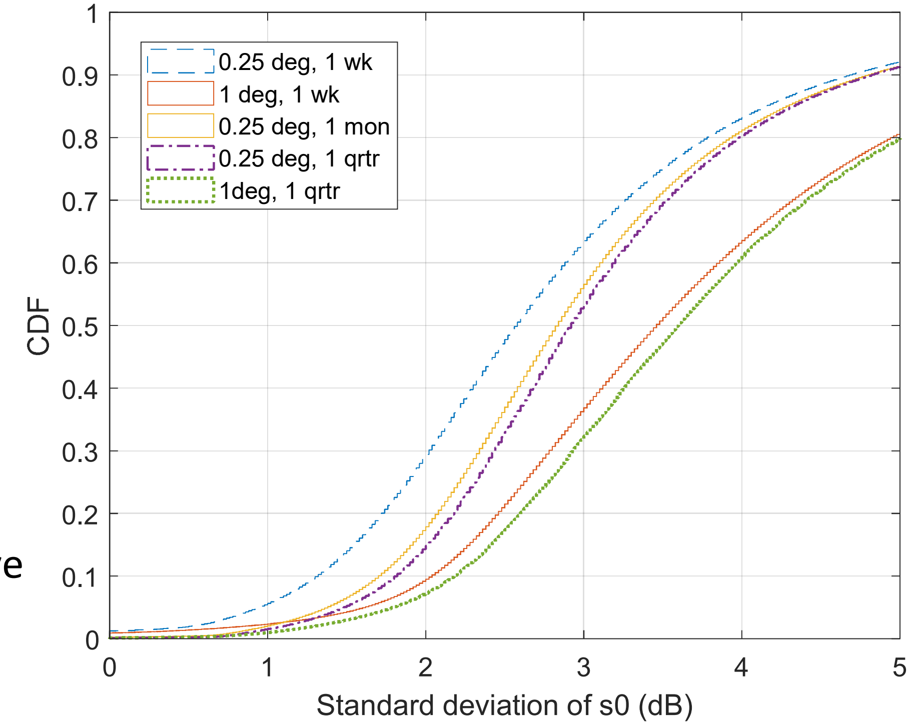
- Mean SD 3.87
- SD of SD 1.56
- Max of SD 12.58





Sigma0 Std Dev versus Resolution

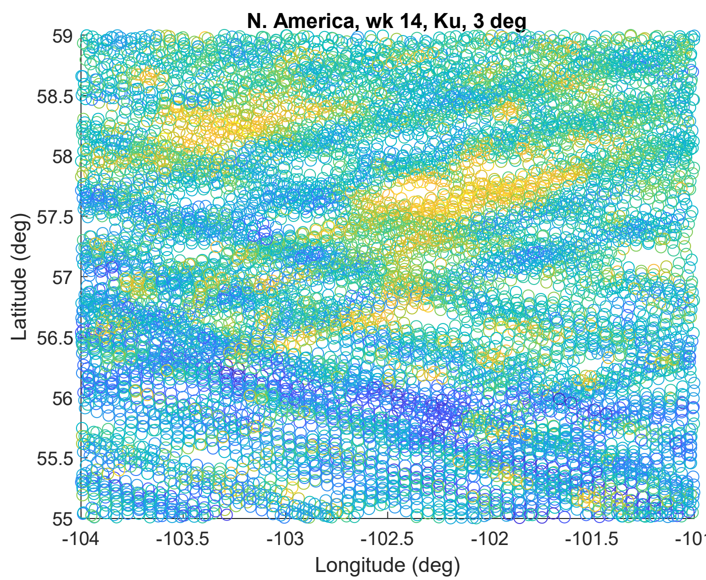
- Plot at right is CDF of standard deviation for different averaging; analogous to Fig. 6 in Meneghini and Jones
- Results indicate that findings of Meneghini and Jones (2011) apply to both space and time
- If we have IID random variables our estimate of the mean becomes more accurate as we increase N; if we start including variables with different means, estimator variance can increase
  - Sample var gets extra term due to difference of means
- Suggests generalization of Meneghini and Kim (2017) to adaptively handle time as well as space
- We already knew that we wanted the database to have high resolution, ideally 0.1 deg and monthly like TRMM, but we are short on measurements (Ka outer)
  - Are there other methods for generating grid estimates from randomly located measurements?
  - For Ka-band outer beam, can we supplement with Ku-band (making use of Ku/Ka correlation)?
  - Adaptive increase of averaging over angle?

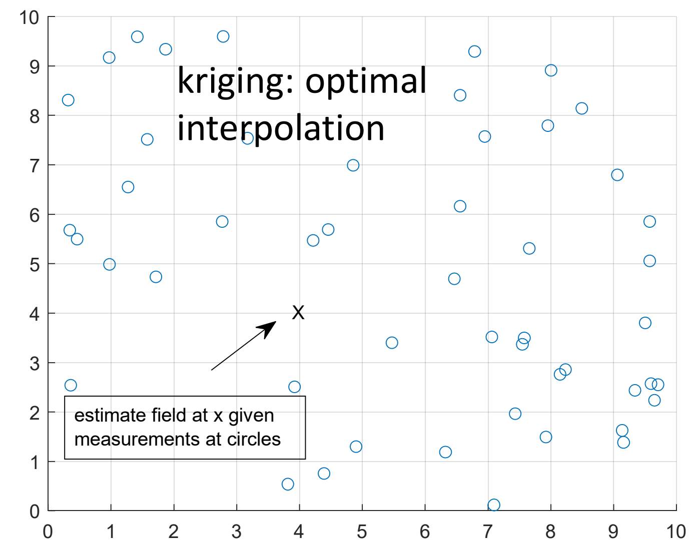


Other methods for estimating field at grid locations: kriging

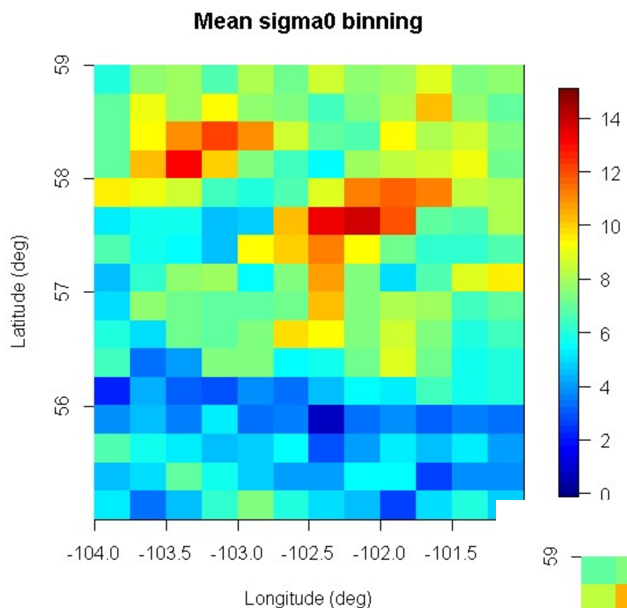
- Have done a brief look at kriging (optimal interpolation) and comparison with the adaptive averaging of Meneghini and Kim 2017
- Consider space only to allow visualization, see figures below; methods are
  - Simple binning: all measurements in an area are considered realizations of single RV, so just average; used for DPR database, relatively fast
  - Distance weighting: as above but give points closer to grid point higher weight; requires distance computation, experiments haven't shown significant improvement
  - Various flavors of kriging (geostats, aka OI in meteorology, Wiener filtering in EE)

- Point measurements of sigma0 for week 14 in the year; orbital patterns are evident
- Kriging takes such data and optimally interpolates to a grid (cartoon at right)

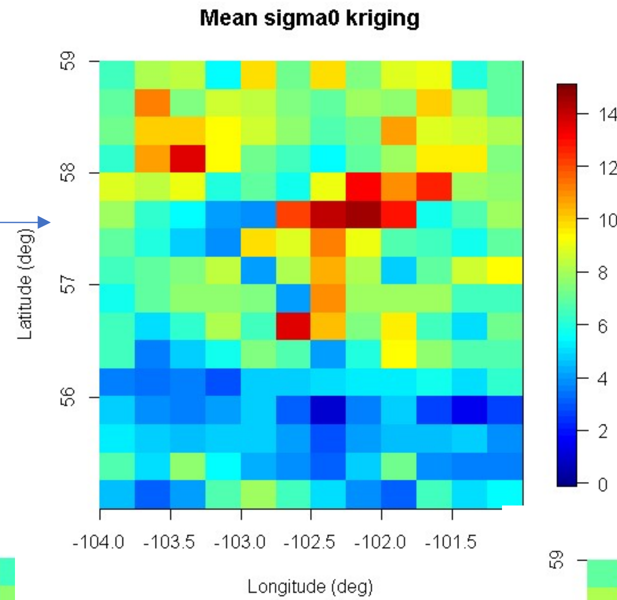


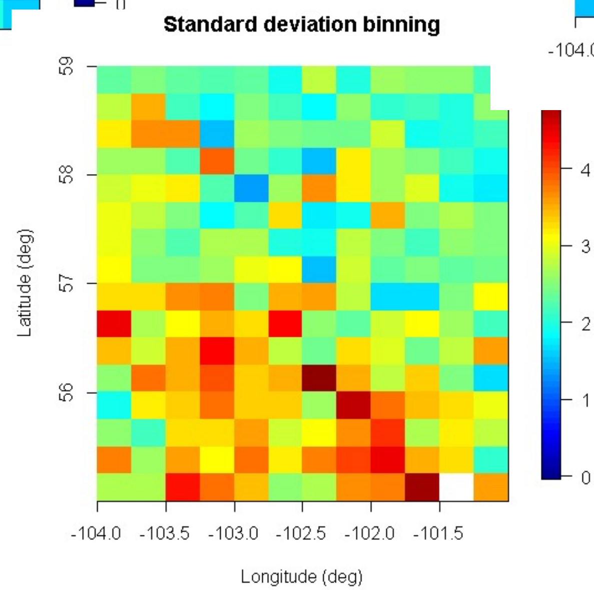


Kriging versus Binning on Example



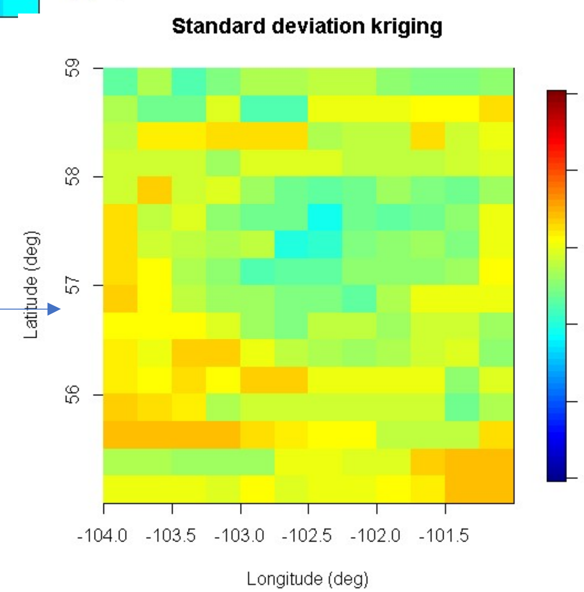
similar means





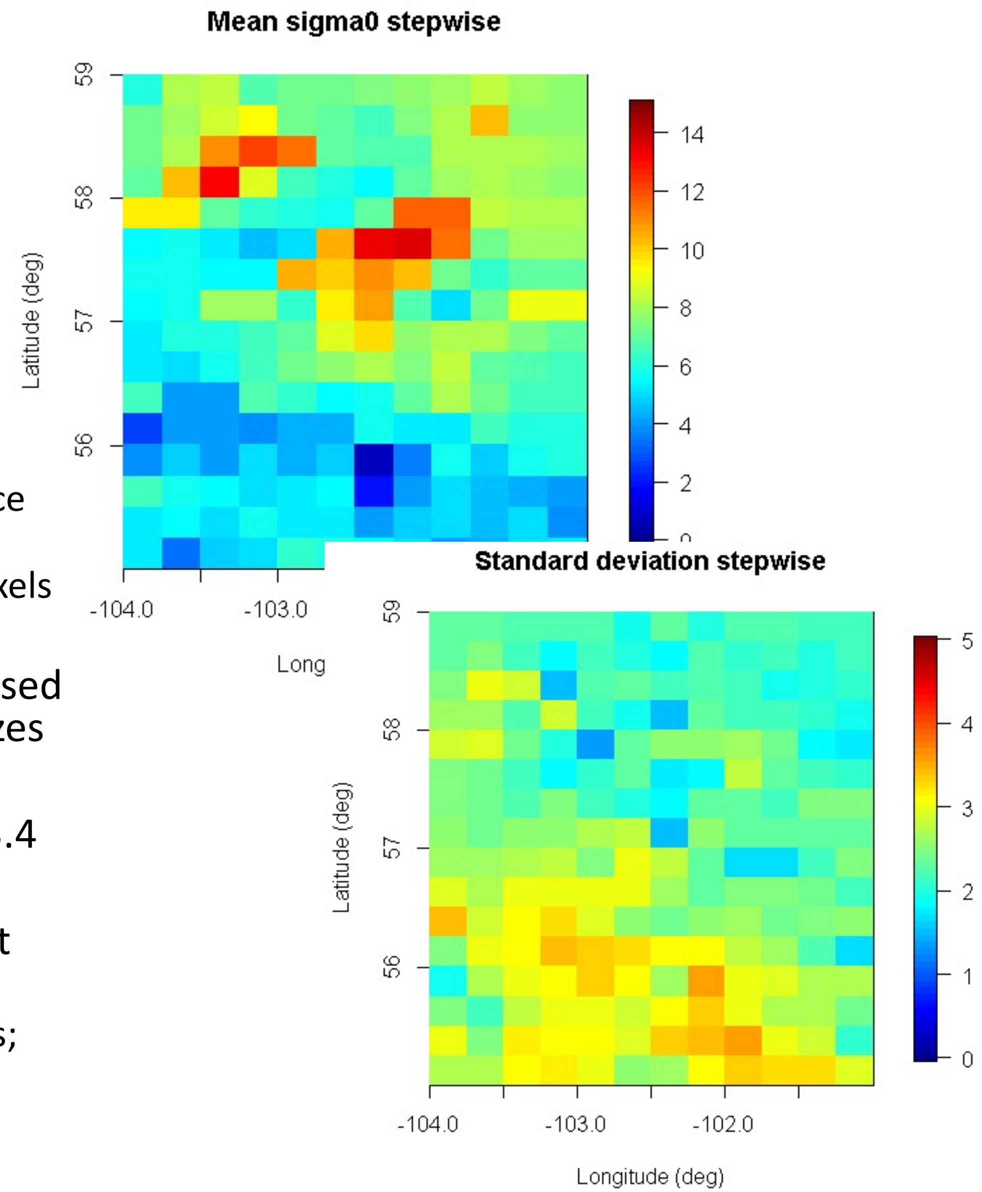
Interpolation grid is 0.25 deg

Standard deviation for kriging is smaller in this case



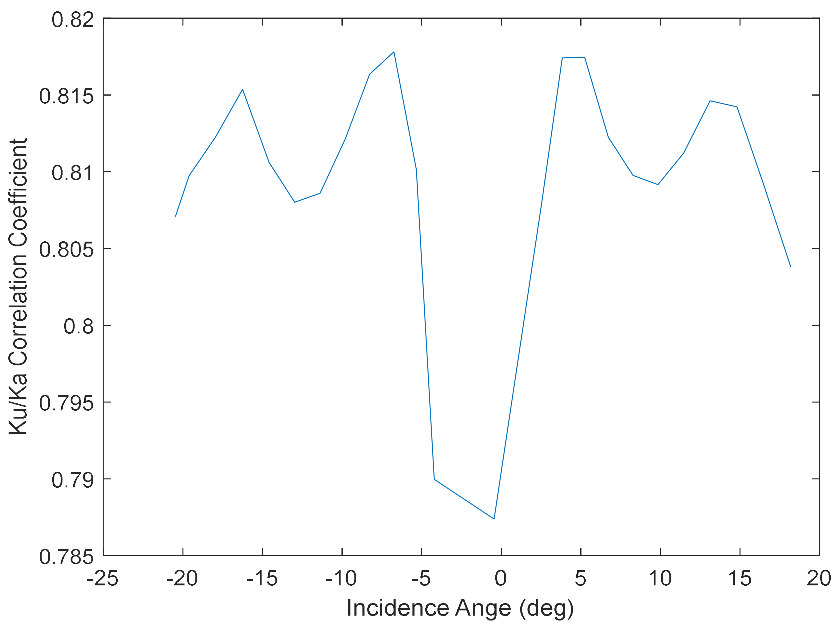
Stepwise binning versus kriging

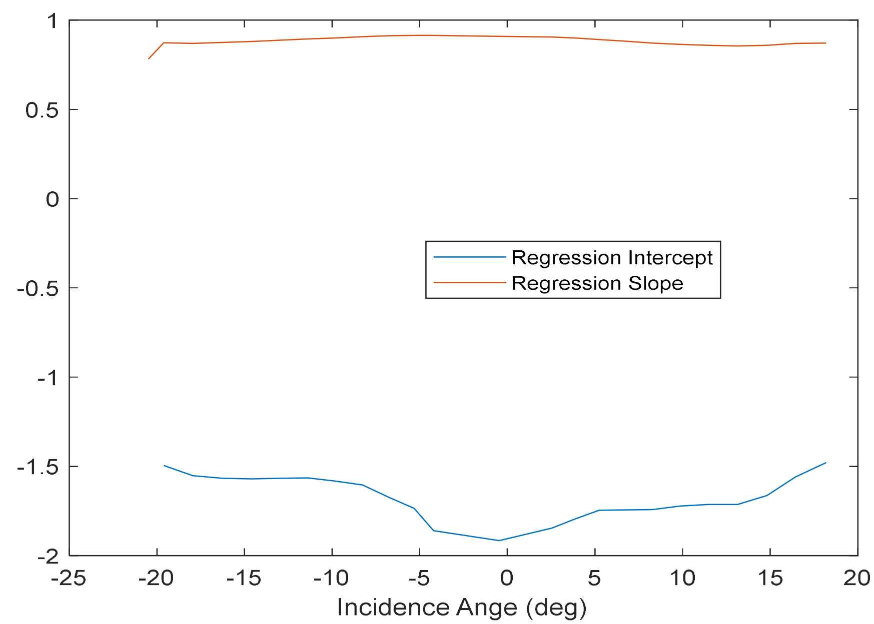
- Also implemented R version of stepwise algorithm in R
- Starts with standard binning at 0.25^{o} resolution
- Loop over lat/lon in the binned data
  - Build list of neighbors
  - Check each neighbor to see whether it increases or decreases variance
  - If increases, stop and use the previous mean and variance for the point
  - If increases, add neighbor to cluster of homogeneous pixels for this point and tre-evaluate neighbors
- Result is that mean and variance for each location is based on averaging over an area around location that minimizes variance
- Max standard deviation of 3.6 dB for stepwise, versus 3.4 for kriging
- Stepwise seems good approximation for kriging, since it also minimizes variance
  - Starts with binned data rather than point measurements; ~20 times faster than kriging



Ku/Ka Correlation and Ka-band Outer Swath Database

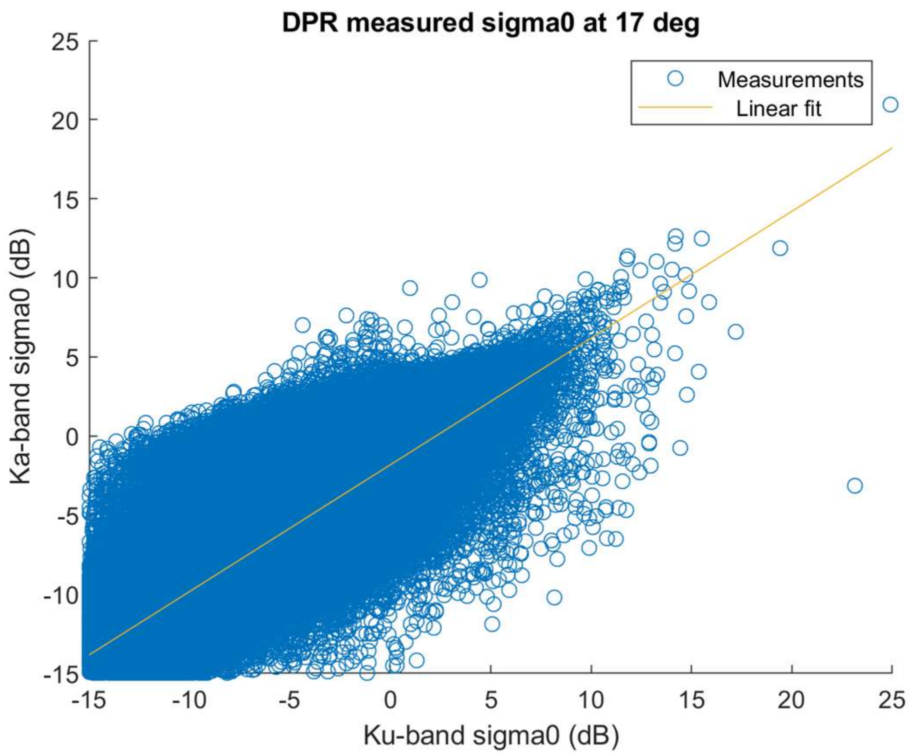
- Two observations about the outer swath data
  - We have many more Ku-band outer swath measurements than we do for Ka-band
  - Sigma0 at the two frequencies is generally well-correlated (basis of DF-SRT)
- Hence, can we use Ku-band sigma0 to estimate Ka-band and so increase the number of Ka-band outer-swath observations?
- Initially looked at Ku/Ka correlation with APR3 airborne data





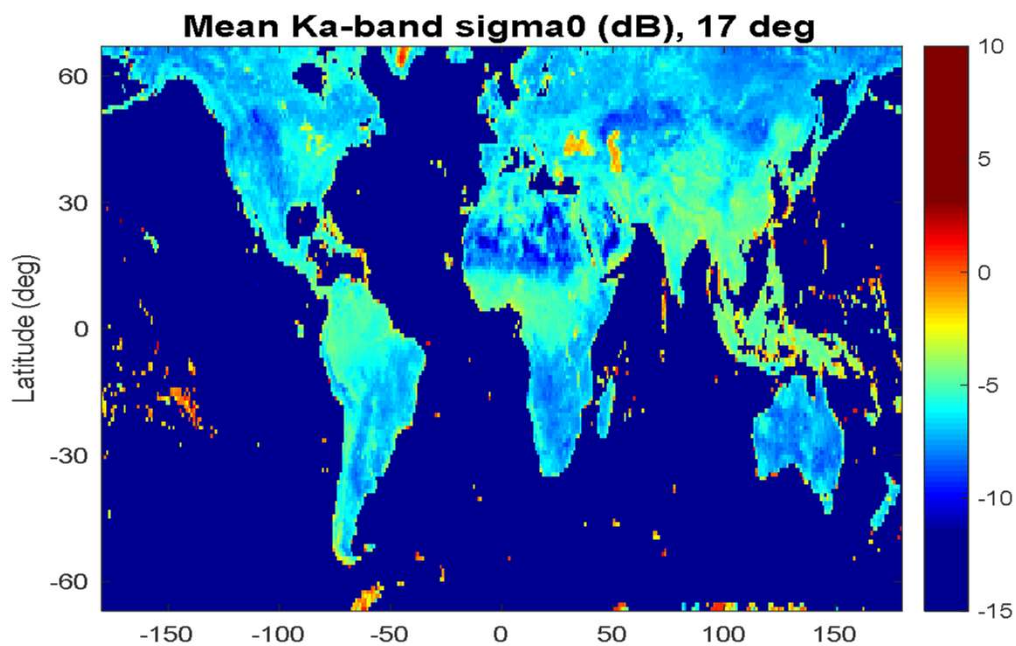
DPR Ku-Ka sigma0 Correlation and Linear Regression

- Version 06X data for outer swath over one month
- As with APR3, computed linear correlation coefficient and linear regression for several angles in outer swath
- Regression line is Ka = slope * Ku + offset
- Results: 11°
  - Correlation coefficient 0.95
  - Regression slope 0.91
  - Offset -1.29
- Results: 14°
  - Correlation coefficient 0.91
  - Regression slope 0.85
  - Offset -1.58
- Results: 17°
  - Correlation coefficient 0.84
  - Regression slope 0.80
  - Offset -1.81
- The RMS error is estimating Ka-band from Ku is 1.2 dB at 17°



Use Ku-band Sigma0 to Estimate Ka-band over Land

- The analysis on previous slide suggests that including Ka-band estimates from Ku-band is feasible
- Tested general idea with V06X data
  - Get sigma0 at both frequencies at 17^{o} incidence
  - Discard 2/3 of the Ka-band measurements and find mean sigma0 at 1^{o} resolution
  - Repeat but combine this estimate with estimate based on regression relationship giving sigma0_Ka versus sigma0_Ku; resulting sigma0 image at right
  - The sigma0 standard deviation in a lat/lon bin is, on average, reduced by only ~0.2 dB
  - However, we do get Ka-band estimates at points where there are no Ka-band measurements
- Theory, along with this simple experiment indicate that including Ku-band data has the potential of improving Ka-band sigma0 estimates
- **However,** improvement relies on very accurate estimate of Ka-band from Ku-band
- Global regressions on previous slide are probably insufficient; also, does this remove improvement using DFR
- Currently focusing on more general problem of understanding sigma0 space/time behavior



Summary

- Need a high res (spatial and temporal) database to reduce SRT PIA errors
- Averaging over larger time intervals is analogous to Meneghini and Jones (2011) finding for space, although improvements of 1 month versus quarterly are relatively small on average
- May be better to stay quarterly in time and reduce spatial averaging as we get more data
- Investigated various methods for generating the database, i.e., estimating a field at grid points from a surrounding cloud of measurements
  - The adaptive approach of Meneghini and Kim (2017) attempts to minimize variance and so appears similar to kriging; experiment on small area of data shows similar std dev
- Explored possibility of using Ku-band to estimate Ka-band; estimator needs to be nearly unbiased locally to avoid increasing variance
- DPR sigma0 appears sensitive to snow melt, surface water/moisture, vegetation, etc., so has utility in surface and land use classification